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Nudges and digital banking adoption

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Abstract

A behavioral literature suggests that nudges can elicit desirable behavior without obvious coercion. Using ATM closures in a dense city as an instrument for minor frictions to physical banking access, we show that affected customers' travel distance to ATMs increases and their ATM activity declines. Importantly, this small friction induces them to increase their usage of the bank's digital platform. Other spillover effects include increases in point-of-sale (POS) transactions, electronic funds transfers, automatic bill payments and savings, and a reduction in cash usage. Our results show that minor frictions can help overcome the status-quo bias and facilitate significant behavior change.

Keywords: Nudge; Digital Banking; FinTech; Geography; Household Finance; Financial Inclusion

JEL Classification Codes: D12, D14, G21, G40, O33

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1. Introduction

A literature in behavioral science proposes that small modifications to a person's choice set can significantly alter behavior without obvious coercion. For example, how a set of investment choices are offered can have a large impact on an investor's decision making (Benartzi and Thaler (2001); Madrian and Shea (2001); and Thaler and Benartzi (2004)). Cronqvist, Thaler, and Yu (2018)) recently show that such nudges can have long-lasting effects. In health science, Thorndike et al. (2012) and Vandenbroele et al. (2020) show that minor changes to physical accessibility can help consumers unknowingly make healthier food choices. The key idea is that innocuous changes to the landscape have the potential to encourage desirable behavior. Benartzi et al. (2017) propose that governments should employ more of such "nudge" tools to influence people's decisions, instead of the usual and more costly sweeping policy interventions.

In this paper, we examine the impact of such choice architecture in influencing digital banking adoption. Traditional banks, now competing with new entrants, have transformed their business strategy—adding digital means to deliver banking services. Digital banking is cheaper and can enable greater financial inclusion beyond the usual geographical reach of physical locations. Philippon (2016) argues that new financial technology (FinTech) gives incumbents an opportunity to reduce historically high financial intermediation costs. Recent studies also attest to the benefits of FinTech, such as increasing savings (e.g., Bachas, Gertler, Higgins, and Seira (2020)), business growth (e.g., Higgins (2019); Agarwal, Qian, Yeung, and Zou (2019); Beck, Pamuk, Ramrattan, and Uras (2018); and Hau, Huang, Shan, and Sheng (2017)), attentiveness to accounts (e.g., Carlin, Olafsson, and Pagel (2019)), and the potential of using digital footprints to improve access to credit (e.g., Berg, Burg, Gombovi, and Puri (2020)).

As documented in the literature, desirable behavioral change can arise from pull or push factors. For pull factors, Cole, Sampson, and Zia (2011) find that very small subsidies can greatly increase the demand for financial services, and Cookson (2018) shows that adding a lottery feature into savings accounts can significantly influence savings behavior. For push factors, Agarwal, Alok, Ghosh, Ghosh, Piskorski, and Seru (2017) and Chopra, Prabhala, and Tantri (2018) show that the 2016 large-scale removal of cash in India forced customers to move to digital means of banking. Larcom, Rauch, and Willems (2017) describe how a London Underground strike in 2014 pushed commuters to experiment with new routes and this led to lasting change in behavior and improvements in route selection.

Our paper focuses on how push factors in physical architecture can elicit behavioral change—but the key distinction is that we do not examine a push but only a *nudge*. The nudge is an ATM closure. In a densely populated city, an ATM closure might impose only a minor physical friction as the next available ATM could be less than 100 meters away. Might such small frictions be sufficient to induce digital banking adoption and other spillover effects of FinTech? Obviously, if there is some pandemic-induced lockdown that completely removes physical banking access, customers will be forced to do their banking online. Our paper is not about such shutdowns, which might achieve the desirable side effect of technology adoption but will be associated with many other negative consequences. The main contribution of our paper is to examine the impact that *minor* physical frictions have in inducing both substitution and spillover effects in the consumer banking industry.

Using a representative sample of 500,000 retail customers of DBS Bank, the largest bank in Singapore, from 2015–2017, we show that customers who experience ATM closures face a modest increase of about 100 meters in their average usage distance to an ATM. We use this closure-induced distance change as an instrument and show that the number of ATM transactions goes down, and importantly, an affected customer's use of the bank's digital platform increases relative to other customers who did not experience such closures. For example, for every 1 km increase in distance, the number and dollar amount of digital transactions increase by 27% and 38% respectively, compared to those of non-treated customers.[1] This substitution effect is stronger for younger customers. This shock also affects other important and interest-

[1] All our results include customer fixed effects and year-month fixed effects, which control for customer heterogeneity and the increasing adoption of digital banking over time. Our results are also robust to alternative measures of distance (by incorporating the approximate workplace location), and a propensity score-matching procedure.

ing dimensions of banking technology adoption—point-of-sale transactions increase, electronic funds transfer transactions increase, automatic bill payments increase, and automatic savings transactions increase, and cash usage declines. Overall, the nudge provided by not finding a formerly used ATM results not only in more engagement with the bank's digital banking platform, but also induces positive spillover to other financial behavior.

The ATM closures that we examine in our paper can occur for two reasons, either an endogenous operations optimization decision by the bank, or a quasi-exogenous temporary closure due to renovations in the facility (e.g. mall) where the ATM is located. We show that for both types of closures, there is little decline in activity at the ATM just before its closure, indicating that the closure is indeed a shock for the affected customers. Importantly, our findings hold for both permanent and temporary closures. They also have a long-lasting effect, i.e. they do not dissipate even when the temporary closures are reopened. This is consistent with Larcom et al. (2017)'s findings that an involuntary re-optimization caused by a temporary shock can result in permanent behavior change.

We believe these results speak to the current issue of banks downsizing their physical locations. Banks frequently cite changed customer behavior as the justification for downsizing. For example, Deutsche Bank plans to close one in five branches in Germany offering the reason that the coronavirus pandemic has driven more customers online.[2] Our study provides the first scientific evidence that the causality might also run in the opposite direction—that even slight reductions in physical access can nudge customers towards digital banking.

Second, our findings add to the literature describing the benefits of FinTech adoption. As some of ATM closures in our sample are quasi-exogenous, their spillover effects can be interpreted as stemming from nudge-induced FinTech adoption. Such "involuntary" adoption should be classified differently from FinTech adoption that is driven by large-scale roll outs. Unsurprisingly, at-scale initiatives have been associated with widespread effects/benefits. For example, Higgins (2019) and Bachas, Gertler, Higgins, and Seira (2020) document the spillover

[2]https://www.ft.com/content/fc1988d2-213f-491e-9194-5e2e91f8ea67, Deutsche Bank plans to close 1 in 5 branches in Germany. German lender responds as coronavirus pandemic drives more customers online.

benefits of a policy-driven debit card distribution program, Agarwal, Qian, Ren, Tsai, and Yeung (2020b) show the impact on business growth by the introduction of a new mobile payments technology, and Agarwal, Ghosh, Li, Huang, and Ruan (2020a) show the impact of India's 2016 demonetization on FinTech use and consumption. The FinTech adoption documented by our study are driven not by such large-scale initiatives but instead by nudges associated with ATM closures. And surprisingly, they also produce significant technology adoption, and spillovers to desirable financial behavior such as more efficient management of account balances and savings.

Third, our findings relate to the importance of geography in financial markets. Geography is important in many areas of finance, for example, the home or familiarity bias of investment (Grinblatt and Keloharju (2001) and Coval and Moskowitz (1999)), accuracy of sell-side research (Malloy (2005)), dividend policy (John, Knyazeva, and Knyazeva (2011)), and even financial misconduct (Parsons, Sulaeman, and Titman (2018)). In corporate banking, distance to a bank is related to corporate loan pricing due to information asymmetry (e.g., Herpfer, Mjos, and Schmidt (2018); Agarwal and Hauswald (2010); and Degryse and Ongena (2005)). In consumer banking, Lippi and Secchi (2009) model the role for the density of bank branches and ATM networks on an agent's cash holding choices, and Bachas, Gertler, Higgins, and Seira (2018) describe physical distance as a transaction cost in consumer banking. Our key finding is that shocks to the ease of accessing ATM services (in the form of a disappearance of an often-used ATM) can produce spillover benefits to banking behavior. The key source of this friction is an agent's geographical preference for closer distances compared to longer distances. Given that our evidence is based on a densely populated city, we believe that the magnitude of such impact is likely a lower bound when it is extrapolated to less dense cities.

Fourth, our findings extend the literature on nudge economics. Kahneman, Knetsch, and Thaler (1991) show that investors exhibit the status quo bias and even the simple switch of a default option can have large effects on the eventual action taken. In a city where ATMs are readily available in adjacent buildings, we show that small nudges in the form of a slight increase in distance can nudge customers to move more towards digital banking.

The rest of the paper is organized as follows. Section 2 describes the data and sample, Section 3 describes the summary statistics and the ATM closure measures, Section 4 reports the empirical results, Section 5 reported additional results and robustness tests, and Section 6 concludes.

2. Data and Sample

2.1. Retail Banking in Singapore

Before describing the Singapore banking data, we provide some background on the banking landscape in Singapore. Singapore is a developed city-country with 5.5 million residents in our sample period of 2015–2017. Its banking industry is dominated by three local banks. Although there are foreign banks that compete for retail deposits, foreign banks face restrictions on their total number of physical locations. In contrast, using network sharing, each of the local banks provides a huge network of ATMs for their customers. A typical local bank's customer has access to about 1,000 ATMs in the country's small land area of 721.5 square km.[3] Singapore's central bank estimates that the majority of the population has access to an ATM within 1 km of their residence.[4] Figure 1 shows a map of Singapore where the dots indicate the locations of the ATMs of DBS, the bank that provided our sample. Banking customers are also well served by bank branches, with each local bank having more than fifty branches during this period.

In terms of FinTech adoption, cash reliance is still high in Singapore in this period even though there is existing technology for banking and payments to be done electronically. The primary reason for a customer to visit a branch or an ATM is still cash related. Debit and

[3]The three local banks are DBS, UOB, and OCBC. DBS has its own unshared network of about 1,000 ATMs. The other two banks' customers are allowed to use each other's ATMs and in aggregate also are also able to access about 1,000 ATMs in their shared network.

[4]http://www.mas.gov.sg/News-and-Publications/Parliamentary-Replies/2017/Reply-to-parliamentary-question-on-accessibility-of-ATMs.aspx

credit cards are widespread and customers are able to use these as payment methods for the majority of merchants. However, a significant fraction of small businesses continue to use cash as the only means of payment so as to avoid the fees associated with electronic payments. Checks are still a common payment method for individuals and businesses, even though electronic payment of bills and electronic fund transfer services can be done without fees.

Overall, while the infrastructure for digital banking is mostly in place, digital banking usage is not yet widespread during the sample period. In our random sample of customers, only about two-thirds use the bank's digital platform at least once.

2.2. Sample Description

Our data is from DBS bank from January 2015 to December 2017. Known as a leading financial services company in Asia, DBS is headquartered and listed in Singapore and has a large retail market share in Singapore.[5] Our unique proprietary dataset contains transaction-level banking activity for 500,000 randomly sampled (using the cross-section of customers in 2016) retail customers from the bank's customer base in Singapore.

The data used in this study can be categorized into three parts. First, we have the transaction data of all of a customer's savings and checking accounts with the bank. Second, we have all of the customer's ATM transactions, specifying the ATM location, amount of the transaction, type of usage (withdrawal, deposit, fund transfer, balance enquiry, etc.), and date and time of usage. Finally, we have a large dataset containing all of the customer's digital transactions with the bank. These are either financial in nature, which we define as transactions with non-zero dollar amounts associated with them (such as a funds transfer or a bill payment), or non-financial in nature (e.g., log-ins, viewing an account summary, a transaction enquiry, or a request for an SMS passcode). We believe we are the first study that attempts to link three important dimensions of retail banking at the micro level.

[5]Please see https://www.dbs.com/about-us/ for more information on DBS.

Besides banking data, we have demographics data on each customer, such as their race, marital status, gender, and age. The most important information we need is the mailing address of the customer. To adhere to privacy regulations, the bank provided addresses only at the postal code level and anonymized all customers' original national identifiers with pseudo identifiers. Unlike in the U.S., where a ZIP code identifies a sizable area within a city, the Singapore postal code identifies an address at the building level. Since more than 90% of residents in Singapore live in high-rise apartments, this sufficiently masks actual customer identities within a building. As an additional safeguard, the bank excluded customers associated with postal codes where it had fewer than 50 customers. This screen will exclude low-rise apartments or stand-alone houses from our sample.

The bank provided three January snapshots of the customer's mailing postal code. In Singapore, physical mail is still important and customers typically change their mailing address immediately after moving as mail forwarding service is costly. For movers, since we do not observe the actual month of move, there is noise in the assumed customer location in the non-January months. As customer moves are infrequent in our sample (only 4% of the 2015 customers had a different postal code in any of the subsequent two years), we believe this noise is minimal and unlikely to bias our results.[6]

Since the bank serves a large fraction of the population in Singapore and provides comprehensive banking services, this random sample is likely to be representative of a customer's overall retail banking activity. But we cannot rule out the possibility that a customer maintains accounts with other banks. Hence, to be more certain that the customers we use for our tests use this bank as their main bank, we focus only on customers in the sample period who have either 1) at least one salary credit, *or* 2) auto-debit transactions totalling at least S$20 in at least six of the months in the sample. A salary credit shows a customer is actively using the bank as they elect for this bank to receive an important source of regular income. The presence of auto-debit transactions shows that the account is actively being used for regular

[6] Our robustness tests will include an alternative cluster-based distance measure that estimates a customer's alternative location anchors such as a new address that was not declared in a timely manner to the bank.

payments and can also capture customers who might have regular income not flagged as a salary credit, e.g. freelancing income, landlord income, retirement income, or contributions by family members.[7]

We also exclude customers who hold any joint-named accounts. Multiple single-named accounts are fine as the variables in each account can be aggregated to the customer level. But joint accounts are tricky to deal with because we cannot tell which of the joint account holders are invoking the auto-debits or receiving the salary credits, even though we can observe ATM and digital activity at the individual level. After imposing these screens, our final sample consists of 197,028 customers. The drop in sample size from the original 500,000 comes mainly from the salary credit, auto-debit, and non-joint account screens. This final sample is about 3% of total population in Singapore in 2015.

3. Summary Statistics

3.1. Distance and Banking Measures

Table 1 reports the summary statistics of the variables used for our analysis. Our final sample includes about 6 million customer-month observations from January 2015 to December 2017. Panel A reports demographic characteristics of age, monthly salary, and the beginning-month account balance. The average customer age is 42.18. The average monthly salary of customers is 2,270 Singapore dollars (S$).[8] The average beginning-month balance, summed across all of the customer's accounts, is S$19,090. During our sample period the mean exchange rate is 0.73 US dollars per Singapore dollar.

We define (*Distance to ATM*) as the mean usage distance of a customer to an ATM. To compute this, for each ATM transaction, we obtain the GPS distance between the customer's

[7]In unreported tests, we show that our results also hold if we restrict the sample only to customers who have at least one salary credit in the sample period.

[8]For months in which the customer does not have a salary credit, their salary is assumed to be zero

postal code and the ATM location postal code.[9] The customer's average ATM usage distance each month is weighted by the number of transactions at each ATM. If we cannot measure the distance for a customer due to no ATM usage in a month, we replace it with the most recent distance of the customer when available (13% of customer-months contain such filled distance measures). The average *Distance to ATM* for a customer-month is 5.08 km.

How do we interpret this mean distance? While customers always have an ATM located close to their homes, they can also use ATMs when they are at other locations such as at a shopping mall or a transport hub. Our average weighs the importance of each location to a customer using the number of transactions.[10] A disadvantage of this home-address based distance measure is that customers could also cluster their activity not just around their home, but around their workplace or some alternative location such as a favorite mall. Unfortunately the customer is not required to register such alternative locations to the bank. Hence, while our baseline tests use the home-based distance measure, we also compute a cluster-based distance measure in robustness tests. We proxy for alternative clusters by choosing the top three geographical centers of a customer's clusters of ATM transactions (we impose a maximum of five clusters in the estimation). With these three cluster centers as alternative locations of the customer, in addition to the home address, we can have up to four addresses for each customer. The alternative measure, *Distance to ATM (Clustered)* is the minimum distance between the used ATM location and any of these four locations. The last row of Panel A shows that this variable averages 1.96 km—unsurprisingly lower than the 5 km average obtained when distance is measured relative to only the customer-provided address.

Panel B reports statistics of various customer banking activity. For ATM activity, we report the total number of transactions, the number of non-financial transactions, and the average dollar amount of an ATM transaction. On average, a customer does 8.26 total ATM transactions per month. Non-financial ATM transactions, i.e. balance enquiry or password

[9]Postal codes are converted to latitudes and longitudes using www.gps-coordinates.net or Google Maps.

[10]We obtain similar average distances if we weigh the importance of each location with the absolute dollar amount transacted instead. The disadvantage of using dollar weights is that we would not be able to include transactions that do not have dollar amounts associated with them, such as a balance enquiry.

change, occur 1.26 times per month. A financial transaction at an ATM, defined as transactions that are associated with a non-zero dollar amount, have a mean amount of S$372 (the median cash transacted is S$200).

For digital activity, we report the total number of transactions, number of financial transactions, and the sum of dollars transacted in a month. On average, a customer does 26.87 digital transactions per month, which includes 2.5 financial transactions (defined by transactions that are associated with non-zero amounts). Total summed dollar amount of financial digital transactions done in a month is S$2,036 per month on average. Note that the averages are computed by setting non-digital users' usage activity and amounts to zero.

We report the total number account-level transactions as a proxy for their overall banking activity with the bank. This counts the total number of transactions across the customer's savings and checking accounts. Savings accounts form the majority (more than 90%) of account activity. The average number of account-level transactions is 27.54 per month.

We also report the descriptive statistics of other outcome variables. Note that the variables take a value of zero if there are no transactions for that variable. The amounts associated are the sum of dollars transacted in a month. The average number of point-of-sale (POS) transactions is 8.76 for a customer-month and the average total POS amount in a month is S$816.94. The average number of regular funds transfers made by a customer is 2.54 and the average total amount transferred in a month is S$1,825.53. Because a regular funds transfer takes 2–3 days to clear, a new method known as Fast And Secure Transfers (FAST) that enables customers to transfer funds from one bank to another almost instantaneously was introduced in 2014. The average number of such FAST transfers made is 0.75 per month in our sample period and the average total amount transferred in a month is S$878.45.

Next, we report the number and mean of auto-debit transactions, which are known as General Interbank Recurring Order (GIRO) transactions. This allows customers to make regular bill payments directly from their bank account to avoid the inconvenience of having to make recurring bill payments manually. We see that the average number of GIRO transactions is 0.70 per month and the average total amount in a month is S$933.

We also proxy for a person's propensity to save using the bank's automatic savings plan called the "Save as You Earn" (SAYE) scheme, where the customer chooses a monthly amount to be deposited to a SAYE account and additional interest is given if there is no withdrawal is made for some specified time period.[11] The average number of SAYE transactions each month is 0.17 and the average total amount saved in a month S$73.54.[12]

The last item in Panel B is the sum of total cash withdrawals in a month, which is S$1,717. This shows that on average, the reliance on cash in this sample period is high.

3.2. Visualizing the ATM Usage Distance

Because our main analysis uses distance as a friction, this section provides visual evidence on how customers access proximate versus distant banking locations.

Figure 2 plots the time-series of the average *Distance to ATM*. We split ATM transactions into three groups: 1) weekday working hours (defined as 8AM–6PM on non public-holiday weekdays), 2) weekday non-working hours, and 3) weekends and public holidays. If the measure correctly captures a customer's physical distance from home to the near-home banking services, the distance should be similar during weekday non-working hours and during weekends/public holidays, both of which are times when the customer is more likely to be at home. In contrast, the distance should be longer during weekday working hours as the customer is more likely to be at work and hence is more likely to use banking services close to their work location. We indeed find that usage distance is longer during working hours. The remarkable similarity between the other two lines plotting the *Distance to ATM* during non-working hours and weekends gives us confidence that the measure correctly picks up the proximity of the customer from their home to their typical banking location.

Although we know that the average distance is 5 km, this does not mean that a customer

[11] https://www.posb.com.sg/personal/deposits/savings-accounts/saye

[12] This amount seems small because the majority of customers do not have such accounts. For non-zero SAYE transactions, the average monthly amount contributed is S$688.31.

prefers ATMs that are exactly at this distance. To see this, we plot a histogram of the probability that a typical customer uses an ATM that is x km away from their postal address. The top chart of Figure 3 shows this plot, where red bars denote the fraction of amounts that a typical customer transacts at ATMs at a particular km. We can see that 40% of a customer's ATM transaction amounts are done at ATMs within the first km from their postal address. The second km is much less important, where the usage fraction declines to less than 10%. This fraction declines further the farther away the ATMs are.[13] To make sure this skewness is not driven by the distribution of ATMs, we plot (with blue bars) as a benchmark the fraction of ATMs that are within x km of a typical customer. One can see that only about 1% of the ATMs in the city are within 1 km of a typical customer but they use these proximate ATMs with a 40% likelihood. This shows the importance of nearness to an ATM.

We have assumed so far that the postal address is the home location. The provided postal codes are indeed associated with residential buildings 90% of the time, with the rest associated with commercial buildings (e.g., an office building).[14] For customers with commercial addresses, which is likely to be their work location, we plot the histogram of their ATM usage in increasing distance from this address in the second chart in Figure 3. We find that the distribution is less skewed compared to the first chart. Although such customers are still more likely to use ATMs close to their work addresses, the strong reliance on the closest ATMs is not as stark. We conclude that the home compared to the work location is a more reliable anchor when customers access ATMs. Also, this means that the distance measure computed from commercial addresses is a noisier proxy for the friction faced by a customer.[15]

Finally, to visualize the usage pattern of an individual customer with reference to their

[13] To match this histogram with the 5 km mean we report in the prior figure, one can take the weighted average of the km value in each bin using the fraction of usage as the weights and this would recover an average of about 5 km. Hence, while the average distance of a typical customer is about 5 km, the most frequently used ATM is the one within the first km. Also note that the longest distance in this histogram is 30+ km which represents a customer with an address at one end of the island (e.g., Tuas at the extreme West of the island) using an ATM at the airport (at the extreme East).

[14] The address category is determined by searching for the postal code with an "(S) " prefix in streetdirectory.com.

[15] This also motivates the use of our alternative cluster-based distance measure as a robustness test that can help detect the other locations that such customers anchor on.

home address, we plot in Figure 4 an ATM usage heatmap by distance. We randomly pick 1,000 customers and arrange them from left to right in the chart in order of increasing mean distance. Each column represents one customer and each cell in a column depicts the probability that the customer uses ATMs at that particular distance, with the red intensity representing a higher usage probability at that particular km. One can see immediately that the lowest-distance customers rely almost exclusively on ATMs within the first km of their address. Second, even the median customer transacts about half of their dollar amounts at ATMs in the first km. Finally, even for far-away customers, the first km retains some importance. Overall, the heatmap shows that customers rely heavily on closer ATMs.

3.3. ATM Closure Measures

To establish a more causal relation between the *Distance to ATM* and customers' banking activity, we need an instrument that changes distance without changing banking activity except through changes in distance. In this paper, we use ATM closure events as a quasi-exogenous shock to distance. A closure is defined as an ATM postal code where no more ATM transactions occur at the postal code for at least 30 days in our sample. Defining ATM closures at the postal code (building) rather than a specific ATM machine avoids the problem that in a large mall, an ATM is closed on one floor, but there is an ATM on another floor. We have 109 closures of ATMs at the postal code level in our sample period.[16] These closures are spread out as shown by the red markers in Figure 1.

These closure events might not be fully exogenous because ATMs are not opened or closed randomly. However, because the density of ATMs is so high in the city, we believe that ATM closures are still useful for studying how customers can be nudged online. From a single affected customer's point of view, the customer uses an ATM because of convenience. On the day that the ATM disappears for this frequent user, the closure could be akin to a random

[16] We do not include the closures of temporary ATMs set up to cater to seasonal demand such as ATMs for Chinese New Year or for the Formula One race event. Usage at such temporary ATMs are also not included when computing the distance measure.

shock for the customer. Second, some of the ATM closures in our sample are strictly not due to the bank's optimization decisions but due to the temporary closure of a malls or office building. For example, Compass One is a sub-urban mall located in the town centre of Sengkang and it was closed for renovation in late October 2015 and re-opened on September 1, 2016. Due to the renovation, the ATM in the mall was closed from September 22, 2015 to September 24, 2016. In such cases, the closure serves as a quasi-exogenous shock to the users of the ATMs at that location. Such temporary closures are more likely to satisfy the exclusion restriction. While our baseline tests combines both types of closures, we will examine temporary and permanent closures separately in a later section.

Panel C of Table 1 reports the summary statistics of the two dummy variables we define to identify customers treated by these ATM closures. The first treated group consists of customers whose favorite (i.e. most used) ATM closes. For this definition, to be certain that that these ATM users are active, we require that the favorite ATM be used at least six times by the customer in the prior three calendar months (i.e. an average of twice a month). This treated group will hence be those who are actually reliant on the ATM before its closure, and are fairly active ATM users in general. The second group consists of customers whose postal address is the nearest to the closed ATM *whether or not* they used the ATM prior to its closure. While this second treated group might overlap with the first group, this measure identifies the set of customers more generally as those who could potentially be affected by the closure. For example, while one might not have used the ATM nearest to them recently, the removal of the *option* for them to use it might have an effect on their behavior.

For the first treated dummy variable, *Post Closure (Favorite ATM)* equals 1 for [0,+] months from the ATM closure event for customers who use this ATM as their favorite, and 0 otherwise. That is, for such treated customers, all months starting from the month of the ATM closure up to the end of the sample period in December 2017 take the value of one. About 3% of our sample is defined as treated using this approach. For the second treated dummy variable, *Post Closure (Nearest ATM)* equals one for [0,+] months from the ATM closure event for customers who are nearest to the ATM, and zero otherwise. About 5% of our sample is defined as treated using this second approach.

4. Empirical Results

4.1. First stage: Impact of Closures on Distance

We have shown that customers are more likely to use banking services very close to where they are located. One can hence view distance as a friction. In a city where ATM density is high, the unavailability of ATMs at one location might induce only a small friction as there are multiple ATMs in the vicinity of the closed ATM. Our goal is to examine whether this minor increase in friction, as proxied by changes to distance induced by the closure, can serve as a nudge towards more digital banking.

In the first stage tests, we examine the effect of ATM closures on *Distance to ATM* using panel regressions reported in Table 2. The dependent variable is *Distance to ATM* and the independent variables are the two measures of closure shock—*Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. We include control variables, namely, the beginning-month account balance in thousands (Beginning Balance), the monthly salary in thousands, year-month fixed effects, and customer fixed effects. Standard errors are clustered at the customer level for this regression and all the other regressions in the paper.

We find that an ATM closure significantly increases *Distance to ATM*. A favorite closure ATM increases post-closure ATM usage distance by 74 meters, about 1.5% of the mean *Distance to ATM*. The closure of the customer's nearest ATM increases their post-closure ATM usage distance by 117 meters, about 2.3% of the mean *Distance to ATM*.

To visualize the results in Table 2, in Figure 5, we plot the residualized *Distance to ATM* around the event month of customers' favorite ATM closure. Note that in the pre-closure period, the mean distance measure includes all of the customer's ATM transactions and not just the transactions at the about-to-close ATM, while in the post-closure period the mean distance measure includes only other ATMs since the treated ATM is now closed. The residualized distance measure is obtained from regressing *Distance to ATM* on *Post Closure (Favorite ATM)*, beginning balance, salary, year-month fixed effects, and customer fixed effects. The average residual from this regression is then plotted in event time around a favorite ATM closure. This Figure 5 plot is hence the abnormal ATM usage distance by a treated customer relative to all other customers, controlling for customer heterogeneity and any time trend in distance. We see an immediate jump of about 0.1 to 0.2 km in *Distance to ATM* at the closure of the customer's favorite ATM. This shows that affected customers face an increase in friction when an often-used ATM closes.[17] Bachas et al. (2018) show that reducing access distance to bank accounts is a good thing for consumers. We show in our setting that ATM closures introduce a distance inconvenience to consumers. Importantly the magnitude of the increase in distance is not large and we can examine if it serves as a nudge towards digital banking.

4.2. Impact of Distance on Customers' ATM Usage

We first examine if the increased distance friction affects a customer's usage of ATMs. If the friction is real, and the customer is inconvenienced by the missing ATM at their favorite or nearest location, their overall ATM usage activity might decline. We use the ATM closure shocks to estimate an instrumental variable (IV) regression. Table 3 reports the IV regression estimates of the effect of the *Distance to ATM* on customers' ATM usage. We find that treated customers indeed use ATMs less frequently. The dependent variable in Column (1) is the natural log of 1+ the total number of ATM transactions. The main independent variable is the *Distance to ATM* instrumented by both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. As in Table 2, we also include the beginning balance, monthly salary, year-month fixed effects, and customer fixed effects as controls so that we estimate the changes within a customer and control for any sample period time trend. We find that the increase in *Distance to ATM* due to *ATM Closure Shocks* indeed decreases the total number of ATM

[17] Interestingly, the residual distance declines after the first few post-closure months and this could be driven by the customer being better able to locate closer ATMs over time.

transactions. In terms of economic significance, a 1 km increase in *Distance to ATM* reduces the dependent variable by 0.178. Since the average total number of ATM transactions is 8.26 (from Table 1), this is a reduction of 1.51 transactions (exp(log(1+8.26)–0.178)–1=6.75; 8.26–6.75=1.51) and is about 18% of the average.

Column (2) reports the results using the total number of non-financial ATM transactions (e.g., balance enquiries, password changes). We find a significant drop—a 1 km increase in *Distance to ATM* reduces this variable by 0.079. Since the average number of non-financial ATM transactions is 1.26, it is a reduction of 0.17 transactions (exp(log(1+1.26)–0.079)–1=1.09; 1.26–1.09=0.17) and this is about 13% of the average. Column (3) reports the result using the average dollar amount of an ATM transaction. We do not find a significant change in this variable due to the closure shock. Hence the customer is not compensating for the less frequent trips to the ATM with more cash per transaction.

To visualize the effects we report in Table 3, Figure 6 plots in event-time the residualized ATM usage around a favorite ATM closure. Note that these are reduced-form representations of the regression results because Table 3 measures the effect of the closures through the distance measure while Figure 6 plots the direct impact of the closures without going through the distance measure. The residual is from regressing the log of 1+ the total number of ATM transactions on the favorite ATM closure dummy, beginning balance, salary, customer fixed effects, and year-month fixed effects. We find a sharp reduction in the residual number of ATM transactions around the closure event and the drop appears permanent, consistent with the results in Table 3.

Panel B plots the residual of the number of non-financial ATM transactions around the closure of customers' favorite ATM. Panel C plots the residual of the average amount of ATM transactions before and after the closure of a customer's favorite ATM. For these two activity variables, we find a slight increase after closure but overall there is a decline in the post-closure months. This is consistent with customers who face a friction in finding ATMs initially, and when finding one does more on the ATM such as withdrawing a larger amount and performing more ancillary transactions such as the checking of balances. However, in the longer term, ATM activity might decline if it is substituted by digital banking.

4.3. Impact of Distance on Customers' Digital Banking Activity

It may not be surprising to find a reduction of ATM transactions when customers are faced with a longer distance to their available ATMs. The more interesting question we examine is whether there is any substitution to digital banking. Will a minor increase in physical frictions lead to an increase in digital banking activity? This tests the nudge and choice architecture ideas—that small changes in the physical landscape can lead to significant behavioral change.

Table 4 reports the IV regression estimates of the effect of the *Distance to ATM* on a customer's digital banking activity. We find that customers indeed do more digital banking after an ATM closure shock increases their *Distance to ATM*. Columns (1)-(3) report the results on digital banking transactions using *Distance to ATM* with *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the instrumental variables. The dependent variable in Column (1) is the log of 1+ the total number of digital transactions. We find an increase in digital transactions by consumers due to the increase in distance due to ATM closures—a 1 km increase in *Distance to ATM* increases the dependent variable by 0.232. Since the average of the number of digital transactions is 26.87, it is an increase of 7.27 transactions (exp(log(1+26.87)+0.232)–1=34.14; 34.14–26.87=7.27) and this is about 27% of the average.

Column (2) uses the log of 1+ the total number of financial digital transactions as the dependent variable. When we narrow down to financial transactions (i.e. those associated with dollar amounts) in digital platform, we find that a 1 km increase in *Distance to ATM* increases financial digital transactions by 0.121. Since the average of the number of digital transactions is 2.50, this is an increase of 0.45 transactions (exp(log(1+2.5)+0.121)–1=2.95; 2.95–2.50=0.45) and is about 18% of the average.

Column (3) uses the log of 1+ the total dollar amount of digital transactions as the dependent variable. We find that a 1 km increase in *Distance to ATM* increases total dollar amount of digital transactions by 0.381. This implies that the total amount of digital transactions went up by about 38%.[18] The effect on the used amount seems larger than the number of transactions indicating that the amounts per transaction also went up.

Columns (4) reports the results on total number of transactions in the banking accounts associated with the customer, i.e. the number of entries in the person's account statements. This is not the same as the sum of ATM transactions and digital transactions as not every ATM transaction or digital transaction is reflected as an entry in the bank account statement. Using the same closure instruments, we show there is no significant impact on the total number of banking transactions in the account. Assuming that the overall changes in banking transactions can proxy the degree of banking inclusion, the result suggests there is no significant change in terms of financial inclusion in general, or account activeness. Hence, there is no evidence that such ATM closures cause the customer to disengage with the bank.

To visualize the effects we report in Table 4, we plot in Figure 7 the residualized digital usage before and after the closure of a customer's favorite ATM. Again, this is a reduced-form plot that targets the direct impact of the closures without going through the distance measure. Panel A plots the average residual of the total number of digital transactions before and after the closure of a customer's favorite ATM. The residual is estimated in the same manner as in Figure 6 by regressing the outcome measure on controls. We find a sharp increase in the average residual digital banking activity around the ATM closure event. Residual digital banking activity also increases over time after the closure event. Note that this post-closure event-time trend is *not* driven by any sample time trend in digital banking usage as year-month fixed effects are included in the regression that estimates this residual. We also do not see any event-time trend prior to the closure. Panels B and C show similar patterns for the number of financial digital transactions and the total dollar amount of digital transactions after the closure of a customer's favorite ATM.

[18]Since the dollar amounts are larger when compared to the counts of the number of transactions, the adding of one to the amount before the taking of logs does not have much of an impact. So we can use the variable's coefficient as an estimate for the economic significance.

Overall, this section documents the key results of our paper. An ATM closure causes only a slight inconvenience to an affected customer as their distance to ATM increases by about 0.1 km. This magnitude is not large considering that this is a city with a high density of ATMs. However, we see a significant reduction in an affected customer's ATM activity. Importantly, there is evidence of a substitution effect as a corresponding increase in digital banking activity occurs in the post-closure period. This is evidence that an ATM closure serves as a small friction to nudge the customer to the bank's digital platform. This is consistent with a literature in behavioral economics which shows that small changes to the choice architecture can have a significant impact on behavior.

5. Additional Tests and Robustness

In this section, we examine several additional tests. We first investigate how our main results look for permanent versus temporary ATM closures. Second, we investigate the impact of closures on other variables associated with desirable outcomes that relate to financial or digital inclusion. Third, we divide the sample according to different age groups. Fourth, we examine in detail the substitution effect where instead of distance, we use the reduction in ATM activity as an instrument for digital banking usage. Finally, we consider a few alternative methodologies for some of our measures and estimations.

5.1. Temporary and Permanent Closures

Our results have thus far grouped all ATM closures at the 109 postal code locations into one group. However, some closures are temporary and some are permanent. We can proxy for temporary closures by checking whether ATM activity resumes subsequently at the particular postal code after it has ceased. With this method we mark 34 out of the 109 closures as temporary. This is a lower bound on the number of temporary closures because we cannot observe whether end-2017 closures reopened in 2018 as our sample stops in 2017. Of the 34 closures determined as temporary, the average number of days closed is 111, and the shortest closure is 34 days.

Temporary closures in our sample are likely to be motivated by some remodelling of the building or facility. Such closures are likely more exogenous than permanent closures. The concern for permanent closures is that they occur for ATMs which face declining customer traffic and the bank closes these ATMs when the customers using those ATMs are more ready to migrate online. To investigate this, we plot in Figure 8 the average number of transactions at a permanent versus a temporary ATM closure around the closure month.

We see three interesting trends. First, ATMs affected by temporary closures are at busier locations with higher on-average traffic (about 4,500 transactions in the month prior to closure), compared to ATMs affected by permanent closures (about 2,500 transactions in the month prior to closure). This is not surprising since the temporary closures are more likely to be associated with mall renovations and ATMs at such locations likely see more traffic than a typical ATM location. Second, we do not see much evidence that permanent closures are associated with a greater pre-closure decline in ATM activity. Since closures occur in event-month 0, if a permanent closure is preceded by a greater decline in ATM activity, there should be a sharper decline in ATM activity from event month –6 to month –1 for permanent closures compared to temporary closures. However, while there is some decline in ATM activity in this period, this decline appears small in magnitude and does not seem to be different between permanent and temporary closures.

The third trend we see is that for temporary closures, activity in the ATM starts to bounce back after month 0. And within 4 to 5 months the activity recovers but it does not go back up to its initial pre-closure level. This is a useful fact to square up with our main result showing that digital banking activity increases without reversal in the post-shock period. If these results also hold for temporary closures, this would mean that a returning ATM does not move the customer back to traditional banking.

Table 5 reports the results of our main analysis done separately for permanent and temporary closures. To prevent the control group from containing customers affected by the other type of closures, when examining the impact of temporary closures in Panel A we remove from the non-treated group all customers who were in the sample period affected by permanent closures. And vice versa when we examine the impact of permanent closures in Panel B.

The dependent variable in Column (1) is the log of 1+ the total number of ATM transactions. The main independent variable is the *Distance to ATM* instrumented by both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. In both Panels A and B, we find that the increase in *Distance to ATM* due to *ATM Closure Shocks* decreases the total number of ATM transactions. Column (2) uses the log of 1+ the total number of non-financial ATM transactions as the dependent variable. In Panel A, we find a significant drop—a 1 km increase in *Distance to ATM* reduces non-financial ATM transactions by 0.117, while the result in Panel B for permanent closures is insignificant. Column (3) reports estimations with the log of 1+ the average dollar amount of ATM transactions as the dependent variable. We do not find any significant results due to both types of closures and this is consistent with Table 3's findings.

The dependent variable in Column (4) is the log of 1+ the total number of digital transactions. We find an increase in digital transactions by customers in both types of closures. Column (5) uses the log of 1+ the total number of financial digital transactions as the dependent variable and Column (6) uses the log of 1+ the total dollar amount of digital transactions as the dependent variable. These results both indicate that the effects from temporary and permanent closures on digital banking activity are similar.

Overall, we do not find evidence in this section that permanent ATM closures are driving our main results.[19] The results for temporary closures are similar to those on permanent clo-

[19] Agarwal et al. (2020b) who also use data from DBS suggest that some ATMs were closed in 2017 in response to the introduction of mobile payments technology for merchants in the vicinity. However, their definition of ATM closures is based on the number of machines at the district (large area) level while we identify closures as all machines closing at a particular postal code (i.e. one building). Our closures are more likely to be renovation motivated rather than due to slight adjustments by the bank at postal codes with multiple ATMs. In addition, our results are robust when we drop 2017 from our sample. Second, there is no evidence of large scale ATM reductions during our sample period as the total number of postal codes with ATMs actually increased from 700 in January 2015 to 756 in December 2017.

sures. This shows that customers who face temporary closures do not move back to traditional means and reduce their digital banking activity even when the closed ATM reopens. This is consistent with Larcom et al. (2017) who show that an exogenous shock-motivated change towards more optimal behavior does not reverse in the long term.

5.2. Spillover Effect to Other Banking Activity

Thus far, we have shown that the closure-induced increased distance to ATM reduces ATM usage and increases digital transactions in general. We now examine specific outcome variables that are related to desirable digital banking-related behavior. The richness of our banking transactions data allows us to identify various types of financial behavior that can be classified as desirable. We examine the following financial activity as new outcome variables: 1) POS transactions which have been shown (e.g., in Bachas et al. (2020)) to have many positive spillover benefits; 2) Regular funds transfers, which provide a more efficient and less costly method of moving funds compared to using checks or cash; 3) FAST transfers, which provides an instantaneous transfer of funds to another bank without waiting for the 2-3 days that regular fund transfers require; 4) GIRO auto-debit transactions, which make bill payments more efficient; 5) SAYE automatic savings transactions, a proxy for disciplined savings which a desirable financial behavior (see, e.g., Cronqvist and Siegel (2015)); and 6) Total cash withdrawn in a month, where a reduction here is a proxy for better digital savviness.

Table 6 reports the results of second-stage regressions, using the fitted distance's effect on these new outcome variables. As before, we take the natural log of 1+ each measure, for the number of transactions for that measure, as well as the total dollar amount used in a month. The first two columns show that the usage of POS transactions goes up both in its number as well as the total dollar amount used. Inferring the economic magnitude from the dollar amount, we find that the dollar amount of POS transactions increases by 17.3% for a 1 km increase in *Distance to ATM*.

The next set of columns use the number and dollar amount of Regular Funds Transfer transactions as the dependent variables. We find that the usage of Funds Transfer transactions significantly increases. The dollar amount of Transfer transactions increases by 27.6% for a 1 km increase in *Distance to ATM*.

Next we examine a more efficient type of transfers—FAST transfers. Customers are also increasing their number of FAST transactions in response to the distance friction. Using the dollar amount of FAST transactions as the dependent variable. We find that a 1 km increase in *Distance to ATM* increases the amounts of FAST transaction usage by 23.4%.

We then examine the number of GIRO transactions and the dollar amount of GIRO transactions as dependent variables. We find that usage of GIRO transactions increases but we have statistical significance only for the number of GIRO transactions.

The next set of columns use the number and total amount of SAYE transactions as the dependent variables. We find that the number of SAYE transactions increases and the dollar amount of SAYE transactions increases by 7.4% for a 1 km increase in *Distance to ATM*.

Finally, column (11) uses the total amount of cash transacted at an ATM in a month as the dependent variable. We find that the cash usage decreases. The dollar amount of cash transacted at at ATM reduces by 8% for a 1 km increase in *Distance to ATM*.

Overall, we find in this section that the distance friction brings about a significant change in eliciting desirable financial behavior from the affected customers. The nudge from an ATM closure not only increases digital banking activity in general, but this spills over positively to other useful FinTech-related outcome variables like POS transactions, funds transfer services, auto-debit bill payment transactions, automatic saving plan contributions, and a reduction in cash usage.

5.3. Subsamples by Age Group

In Table 7, we estimate the results in Tables 3, 4, and 6 for different age groups. We split our sample into age terciles so that we have an equal number of customers in each group. The first tercile (indicated by 1/3) represents customers under the age of 33 with an average age of 26. The second group (2/3) has customers from ages 34 to 47 with an average age of 40. The third group (3/3) consist of customers above 48 and their average age is 58.

In Columns (1)-(3), we find that the reduction in the number of ATM transactions is the largest among the middle group (2/3) followed by the youngest group (1/3). The oldest group (3/3) shows a slight reduction in the number but without statistical significance. In Columns (4)-(6), we find that the reduction in the number of non-financial ATM transactions are the largest among the youngest group followed by the middle group. The oldest group instead shows an increase in such ATM transactions after the shocks.

For the spillover effect to digital banking, we find that the increase in the number and the amount of digital transactions as a result of the distance friction are the largest in the youngest group (1/3) followed by the middle group (2/3). The oldest group (3/3) also shows an increase in digital transaction but the effects are the weaker compared to the magnitude of the coefficients in the other two groups. These results show that the nudge toward digital banking is more effective for the younger age groups compared to the the oldest age group.

For the other outcome variables, most show that the effects are stronger for the younger age groups, although there are a few mixed results. For example, we find that the increase in FAST transactions is the largest among older groups while the increase of POS transactions shows the opposite ordering. However, the increase in Transfer transactions, GIRO transactions, and SAYE transactions are larger in the youngest group compared to the oldest group. The reduction in cash withdrawal is largest in the middle group while the youngest group and the oldest group show no effect.

We conclude that the substitution from physical to digital facilitated by an ATM-closure nudge appears to affect younger customers more than older customers. It could be that the costs of switching is lower for younger and more tech-savvy customers so that a minor friction is sufficient to induce a substitution effect.

5.4. Substitution Effect between ATM and Digital Transactions

To understand better the source of the above results and whether they are robust, we now do the analysis using another approach where we now target directly the substitution effect—using the decline in ATM activity as the channel by which the substitution to digital channels occurs. This means a first stage estimation where we regress ATM activity on the ATM closure dummies, and then use the fitted value of the ATM activity in the second stage to relate to the new outcome variables. This measures whether the reduction in use of an old financial technology (ATMs) induced by a closure of an ATM, can lead to spillover effects onto other types of desirable financial behavior. In other words, the proxy for friction is no longer distance, but the actual reduction in usage of the older technology is used to proxy for "friction". Such an analysis could also be useful if the distance variable is measured with noise because the friction proxy is now ATM activity itself—if ATM activity declines due to a closure regardless of the distance, it must be that the customer now has more difficulty assessing an ATM.

Table 8 reports the first stage of the effect of ATM closures. The dependent variable is now the log of 1+ the total number of ATM transactions. The main independent variables in Column (1) are *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. As before, other controls include the Beginning Balance, Salary, year-month fixed effects, and customer fixed effects. We find a significant reduction in the total number of ATM transactions from the favorite ATM closures, but the effect from the nearest ATM closures is not significant. Column (2) uses *Post Closure (Favorite ATM)* alone as the shock and finds a significant effect of favorite ATM closures on the total number of ATM transactions. Since only one of the closure shock dummies is significant, we use *Post Closure (Favorite ATM)* as an IV for the changes in total number of ATM transactions.

We now report IV regression estimates of the effect of customers' total number of ATM transactions on digital banking activity as an IV in Table 9. In Columns (1)-(4), the main independent variable is the log of 1+ the number of total ATM transactions, instrumented by *Post Closure (Favorite ATM)*. The dependent variable for Column (1) is the log of 1+ the total number of digital transactions this significantly increases when the total number of ATM transactions decreases. Since both the dependent and independent variables are in logs, the coefficient can be interpreted as the percentage change in the total number of digital transactions when the total number of ATM transactions changes by 1%. A negative coefficient indicates a substitution effect, i.e., a 1% reduction in the total number of ATM transaction leads to a 0.69% increase in the total number of digital transactions.

Column (2) uses the log of 1+ the total number of financial digital transactions and Column (3) uses the log of 1+ the total dollar amount of digital transactions as the dependent variables. We find that a 1% reduction in the total number of ATM transactions leads to a 0.36% increase in the number of financial digital transactions and a 1.00% increase in the dollar amount of digital transactions. In Column (4), we use the log of 1+ the total number of account-level transactions as the dependent variable and we find a significant increase. This implies that the positive spillover to digital banking as a result of the ATM closure more than compensates for the reduction in ATM activity so that the total banking activity as proxied by the number of entries in their banking accounts goes up.

Hence, this section provides additional evidence of the substitution effect. Customers who face a friction because of the ATM closure reduce their ATM activity. This involuntary reduction of ATM activity is then substituted by an increase in digital banking usage.

5.5. A Clustered-Based Distance Measure

Our main results are based on the *Distance to ATM* measure which is defined as the average usage distance between the customer's reported address to the bank and the used ATMs. This ignores the possibility that a customer might anchor not only on their provided address (which we assume to be their home), but also on their workplace or a favorite mall. As described in Section 3, we compute an alternative distance measure which includes up to three new "addresses" for each customer by clustering their ATM usage and choosing the top three cluster centers as additional location anchors. These three new addresses will very likely include their workplace and an additional two other favorite locations. The new *Distance to ATM (Clustered)* measure which relies on the minimum distance between the ATM and any of these three new anchors or the home address has a mean of of 2 km (reported in Table 1) instead of a mean of 5 km of the original *Distance to ATM* measure.

In unreported results, when we regress this new clustered distance measure on the ATM closure shocks, we get a coefficient of 0.084 for the *Post Closure (Favorite ATM)* dummy, and a coefficient of 0.069 for the *Post Closure (Nearest ATM)* dummy. It is not surprising the increase in distance of 69–84 meters is smaller than it was for the baseline distance measure since we are allowing more location anchors for the customer.

Importantly, when we use this new distance measure for our tests, our results (unreported) are still robust—showing that digital banking activity and other financial outcome variables go up because of the distance friction induced by the closure of the ATM. Hence, we believe our results are not sensitive to the lack of a workplace address in our baseline sample.

5.6. Using a Propensity-Score Matched Control Sample

Our main tests use the full panel of customers as the control group and we add customer fixed effects to control for any heterogeneity in observable customer characteristics or unobservable demographics. We believe that using the full panel provides the most power for our tests and the use of fixed effects adequately controls for any observable or unobservable customer characteristics. However, we now explore another way to form the control sample which is to use a targeted group matched on certain characteristics.

We form a propensity-score matched sample by using five lagged-month variables, namely, distance to ATM, number of ATM transactions, number of digital banking transactions, number of account-level transactions, and monthly salary. In the month before closure for each treated customer (i.e. a customer-closure observation associated with either a favorite or a nearest closure shock), we identify another customer who was not affected by any closure but had the closest predicted probability of facing a closure based on these five characteristics. We find similar results (unreported) when the regressions are estimated using only this control sample alongside the treated observations in the resulting smaller panel.

6. Conclusion

A behavioral literature proposes that nudges can induce positive behavioral change. We use novel consumer banking data to examine whether small physical frictions can help nudge customers towards digital banking. Our data comes from a large bank in Singapore from 2015–2017, where we show that in a dense city, ATM closures induce only a small friction to bank customers—increasing their ATM usage distance by about 100 meters. Surprisingly, this minor friction is sufficient to nudge affected customers towards more digital banking activity.

Importantly, the substitution from physical ATM use to digital banking facilitates several important spillover outcomes associated with desirable financial behavior. Treated customers who reduce their usage of ATMs, increase their point-of-sale payments, regular funds transfers, instantaneous funds transfers, and automatic bill payments/savings schemes, and they reduce their cash usage. In terms of cross-sectional differences, these effects are generally stronger for younger age groups. These results add to the literature which shows that new financial technology can have real benefits.

They also provide support for the literature on nudge economics and choice architecture, showing that minor modifications to a person's choice set can elicit desirable behavioral change. The friction here is the physical distance to banking. That minor changes in distances can have such impact shows that physical distance remains an important friction for customers and shocking these distances in a minor way can have significant impact. These results also reveal that the preference of customers to have easier physical access to banking locations can be substituted by digital access to banking, which could provide other spillover benefits.

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Table 1: Summary Statistics

We report summary statistics of the variables for our analysis. Our sample includes customer-month observations from January 2015 to December 2017. Panel A reports the demographic details of our sample's customers, namely their age, monthly salary in S$ thousands, and monthly account beginning balance in S$ thousands. We also report summary statistics for *Distance to ATM* a transaction-weighted distance to their used ATMs from the provided customer address. Panel B reports the customers' banking activity. For their monthly ATM activity, we report the total number of ATM transactions, the number of non-financial transactions, and the mean dollar amount of an transaction. For their monthly digital banking activity, we report the total number of digital transactions, the total number of financial transactions, and sum dollar amount of monthly transactions. We also report the total number of account-level transactions recorded in the customer's savings and checking accounts. For the monthly total of other types of banking transactions, we report number and amount of Point-of-Sale (POS) transactions, Transfer (regular funds transfers) transactions, FAST transactions (instant funds transfers), General Interbank Recurring Order (GIRO) transactions (which are auto-debit bill payments), Save-As-You-Earn (SAYE) automatic savings transactions, and the total amount of cash withdrawn. Panel C reports summary statistics of the ATM Closure Shocks. *Post Closure (Favorite)* equals to 1 from the ATM closure event when the closed ATM is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address.

Variables		Obs	Mean	Std. Dev.	10th	25th	50th	75th	90th
Panel A: Customer Demographics									
Age		5,994,130	42.18	14.49	24	30	41	53	63
Monthly Salary (S$'000)		5,994,130	2.27	5.89	0	0	0.75	3	5.67
Begining Balance (S$'000)		5,994,130	19.09	71.85	0.05	0.5	2.5	11.88	44.1
Distance to ATM		5,994,130	5.08	4.59	0.44	1.36	3.87	7.49	11.54
Distance to ATM (Clustered)		5,994,130	1.96	2.15	0.17	0.49	1.27	2.66	4.66
Panel B: Customers' Banking Activity									
ATM Transactions	Total #	5,994,130	8.26	8.47	1	3	6	11	17
	non-Financial #	5,994,130	1.26	3.5	0	0	0	1	4
	Average S$ per txn	5,994,130	372	1236	50	100	200	416	800
Digital Transactions	Total #	5,994,130	26.87	48.4	0	0	6	38	78
	Financial #	5,994,130	2.5	6.53	0	0	0	3	8
	Monthly Total S$	5,994,130	2036	14068	0	0	0	1140	4539
Total # of Account-level Transactions		5,994,130	27.54	22.03	8	13	23	36	52
Other Transactions (Monthly Total)									
	# of POS Transactions	5,994,130	8.76	11.21	0	2	5	12	22
	S$ of POS Transactions	5,994,130	817	2185	0	58	337	979	2080
	# of Transfer Transactions	5,994,130	2.54	7.26	0	0	1	3	7
	S$ of Transfer Transactions	5,994,130	1825	14613	0	0	2.5	976	3570
	# of FAST Transactions	5,994,130	0.75	2.48	0	0	0	0	2
	S$ of FAST Transactions	5,994,130	878	5978	0	0	0	0	1600
	# of GIRO Transactions	5,994,130	0.7	0.46	0	0	1	1	1
	S$ of GIRO Transactions	5,994,130	933	6328	0	0	168	613	1836
	# of SAYE Transactions	5,994,130	0.17	0.59	0	0	0	0	0
	S$ of SAYE Transactions	5,994,130	73	428	0	0	0	0	0
	S$ of Cash Withdrawal	5,994,130	1717	4045	160	400	1000	2000	3480
Panel C: ATM Closure Shock									
Post Closure (Favorite ATM)		5,994,130	0.03	0.16	0	0	0	0	0
Post Closure (Nearest ATM)		5,994,130	0.05	0.22	0	0	0	0	0

Table 2: The Effect of ATM Closures on the Distance to ATM

We report panel regression estimates of the effect of an ATM Closure Shock on a customer's usage distance to an ATM. The dependent variable is the *Distance to ATM*, a transaction-weighted distance to their used ATMs from the provided customer address. Column (1) uses the *Post Closure (Favorite ATM)* and the *Post Closure (Nearest ATM)* as the main independent variables. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. Coefficient estimates are reported with t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Variables	(1) Distance to ATM
Post Closure (Favorite ATM)	0.074***
	(3.12)
Post Closure (Nearest ATM)	0.117***
	(6.94)
Beginning Balance	0.0002***
	(3.56)
Monthly Salary	0.003***
	(7.85)
Observations	5,994,130
R^2	0.573

Table 3: The Effect of the Distance to ATM on Customers' ATM Usage (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to ATM on a customer's ATM usage using the ATM Closure Shocks as an IV. The main independent variable is *Distance to ATM*, a transaction-weighted distance to ATM used from the provided customer address, instrumented by the ATM Closure Shocks. We use *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. The dependent variable for Column (1) is the natural log of 1+ the Total Number of ATM Transactions, for Column (2) is the log of 1+ the Total Number of non-Financial ATM Transactions, and for Column (3) is the log of 1+ the Average S$ Amount of ATM Transactions. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands., year-month fixed effects, and customer fixed effects. Coefficient estimates are reported with t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Variables	(1) log (1+# of ATM Total Txns)	(2) log (1+# of ATM non-Financial Txns)	(3) log (1+S$ of ATM Txns)
$\widehat{\text{Distance to}}$ ATM	-0.178***	-0.079***	0.013
	(-6.45)	(-2.98)	(0.54)
Beginning Balance	0.0002***	2.16e-05*	0.0005***
	(8.48)	(1.78)	(8.80)
Monthly Salary	0.003***	0.001***	0.003***
	(10.42)	(6.91)	(10.09)
Observations	5,994,130	5,994,130	5,994,130
R^2	0.120	0.474	0.499

Table 4: The Effect of the Distance to ATM on Customers' Digital Banking Activities (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to ATM on customers' Digital Banking Activities using ATM Closure Shocks as an IV. The main independent variable is *Distance to ATM (Raw)*, a transaction-weighted distance to ATMs used from the provided customer address, instrumented by the ATM Closure Shock. We use *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. The dependent variable for Column (1) is the log of 1+ the Total Number of Digital Transactions, for Column (2) is the log of 1+ the Total Number of Financial Digital Transactions, for Column (3) is the log of 1+ the Total S$ Amount of Digital Transactions, and for Column (4) is the log of 1+ the Total Number of Account-level Transactions. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. Coefficient estimates are reported with t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Variables	(1) log(1+# of Digital Total Txns)	(2) log(1+# of Digital Financial Txns)	(3) log(1+S$ of Digital Txns)	(4) log(1+# of Account Txns)
$\widehat{\text{Distance to}}$ ATM	0.232***	0.121***	0.381***	-0.0107
	(4.60)	(4.64)	(4.12)	(-0.63)
Beginning Balance	0.0002***	0.0002***	0.001***	0.0004***
	(5.01)	(7.42)	(8.80)	(9.81)
Monthly Salary	0.004***	0.003***	0.013***	0.005***
	(10.01)	(10.17)	(10.83)	(11.04)
Observations	5,994,130	5,994,130	5,994,130	5,994,130
R^2	0.709	0.646	0.690	0.734

Table 5: Temporary and Permanent ATM Closures (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to ATM on customers' ATM usage and Digital Banking activities using temporary and permanent ATM Closure Shocks as an IV. The main independent variable is *Distance to ATM*, a transaction-weighted distance to ATMs used from the customer-provided address, instrumented by temporary or permanent ATM Closure Shocks. Panel A reports the regression results for temporary closures excluding customers who experienced any permanent closures of their favorite or nearest ATM. Panel B reports the regression results for permanent closures excluding customers who experienced any temporary closures of their favorite or nearest ATM. We use *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. The dependent variable for Column (1) is the log of 1+ the Total Number of ATM Transactions, for Column (2) is the log of 1+ the Total Number of non-Financial ATM Transactions, for Column (3) is the log of 1+ the Average S$ Amount of ATM Transactions, for Column (4) is the log of 1+ the Total Number of Digital Transactions, for Column (5) is the log of 1+ the Total Number of Financial Digital Transactions, and for Column (6) is the log of 1+ the Total Amount of Digital Transactions. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. Reported coefficient estimates have *t*-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Panel A: Temporary ATM Closures

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+# of ATM Txns)		log(1+S$ of	log (1+# of Digital Txns)		log (1+S$ of
Variables	Total	non-Financial	ATM Txns)	Total	Financial	Digital Txns)
$\widehat{\text{Distance to}}$ ATM	-0.269***	-0.117**	-0.067	0.228**	0.115**	0.402**
	(-3.95)	(-1.99)	(-1.37)	(2.38)	(2.35)	(2.23)
Beginning Balance	0.0002***	2.90e-05*	0.0005***	0.0002***	0.0002***	0.001***
	(7.12)	(1.65)	(8.96)	(4.41)	(7.21)	(8.94)
Monthly Salary	0.003***	0.001***	0.003***	0.004***	0.003***	0.012***
	(8.79)	(4.52)	(9.13)	(8.29)	(8.89)	(9.63)
Observations	5,367,297	5,367,297	5,367,297	5,367,297	5,367,297	5,367,297
R^2	0.559	0.338	0.471	0.713	0.661	0.679

Panel B: Permanent ATM Closures

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+# of ATM Txns)		log(1+S$ of	log (1+# of Digital Txns)		log (1+S$ of
Variables	Total	non-Financial	ATM Txns)	Total	Financial	Digital Txns)
$\widehat{\text{Distance to}}$ ATM	-0.115***	-0.024	0.022	0.201***	0.115***	0.366***
	(-4.68)	(-0.90)	(0.84)	(3.76)	(4.03)	(3.62)
Beginning Balance	0.0002***	1.50e-05	0.0005***	0.0002***	0.0002***	0.001***
	(8.39)	(1.27)	(8.33)	(5.03)	(7.08)	(8.40)
Monthly Salary	0.003***	0.001***	0.003***	0.004***	0.003***	0.013***
	(10.03)	(6.05)	(9.61)	(9.68)	(9.71)	(10.36)
Observations	5,609,306	5,609,306	5,609,306	5,609,306	5,609,306	5,609,306
R^2	0.427	0.573	0.495	0.742	0.659	0.696

Table 6: Using other Banking Activity as Outcome Variables (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to ATM on customers' other Banking Activity using ATM Closure Shocks as an IV. Columns (1) and (2) use the monthly number and total S$ amount of POS transactions respectively as the dependent variable. Columns (3) and (4) use the number and S$ amount of Regular Transfer transactions respectively as the dependent variable. Columns (5) and (6) use the number and S$ amount of FAST transactions (instantaneous transfers) respectively as the dependent variable. Columns (7) and (8) use the number and S$ amount of GIRO transactions (auto-debit bill payments) respectively as the dependent variable. Columns (9) and (10) use the number and S$ amount of SAYE transactions (automatic savings transactions) respectively as the dependent variable. And Column (11) uses the total S$ cash amount transacted as the dependent variable. For all outcome measures, we add 1 before taking the natural log. The main independent variable is *Distance to ATM (Raw)*, a transaction-weighted distance to ATMs used from the provided customer address, instrumented by the ATM Closure Shock. We use *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. For brevity, the coefficients of the control variables are not reported. Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Variables	(1) log(1+# of POS Txns)	(2) log(1+S$ of POS Txns)	(3) log(1+# of Transfer Txns)	(4) log(1+S$ of Transfer Txns)
$\widehat{\text{Distance to}}$ ATM	0.096***	0.173***	0.099***	0.276***
	(3.56)	(2.97)	(3.94)	(3.05)

Variables	(5) log(1+# of FAST Txns)	(6) log(1+S$ of FAST Txns)	(7) log(1+# of GIRO Txns)	(8) log(1+S$ of GIRO Txns)
$\widehat{\text{Distance to}}$ ATM	0.058***	0.234**	0.016*	0.126
	(2.86)	(2.55)	(1.70)	(1.59)

Variables	(9) log(1+# of SAYE Txns)	(10) log(1+S$ of SAYE Txns)	(11) log(1+S$ of Cash Withdrawal)
$\widehat{\text{Distance to}}$ ATM	0.013**	0.074**	-0.080***
	(2.11)	(2.09)	(-2.58)

Table 7: Results according to Age Groups (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to ATM on customers' ATM usage, Digital Banking activity, and other Banking Activity using ATM Closure Shocks as an IV in age group terciles subsamples. In Columns (1)-(3), the dependent variable is log of 1+ the Total Number of ATM Transactions. Column (1) reports the result of youngest tercile group (1/3), Column (2) reports the result of middle tercile group (2/3), and Column (3) reports the result of oldest tercile group (3/3). The main independent variable is the *Distance to ATM*, instrumented by *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. For brevity, the coefficients of the control variables are not reported. Other dependent variables are the log of 1+ the number of non-financial ATM transactions (Columns (4)-(6)), the log of 1+ the number of total digital transactions (Columns (7)-(9)), the log of 1+ the number of financial digital transactions (Columns (10)-(12)), the log of 1+ the S$ amount of digital transactions (Columns (13)-(15)), the log of 1+ the number of FAST transactions (Columns (16)-(18)), the log of 1+ the number of POS transactions (Columns (19)-(21)), the log of 1+ the number of Transfer transactions (Columns (22)-(24)), the log of 1+ the number of SAYE transactions (Columns (25)-(27)), the log of 1+ the number of GIRO transactions (Columns (28)-(30)), and the log of 1+ the S$ amount of total monthly cash transacted at an ATM (Columns (31)-(33)). Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age Groups	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3
Variables	log(1+# of Total ATM Txns)			log(1+# of non-Fin ATM Txns)			log(1+# of Total Digital Txns)			log(1+# of Fin Digital Txns)		
$\widehat{\text{Distance to}}$ ATM	-0.234***	-0.272***	-0.043	-0.318***	-0.104*	0.138***	0.434***	0.300***	0.113**	0.256***	0.153***	0.036
	(-3.88)	(-3.95)	(-1.50)	(-3.99)	(-1.91)	(2.94)	(3.46)	(2.80)	(2.03)	(3.63)	(2.72)	(1.51)

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Age Groups	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3
Variables	log(1+S$ of Digital Txns)			log(1+# of POS Txns)			log(1+# of Transfer Txns)			log(1+# of FAST Txns)		
$\widehat{\text{Distance to}}$ ATM	0.715***	0.524**	0.148	0.161***	0.112**	0.080**	0.201***	0.134**	0.040	0.026	0.111**	0.052**
	(3.30)	(2.57)	(1.56)	(0.74)	(2.42)	(2.03)	(2.82)	(2.14)	(2.35)	(3.27)	(2.55)	(1.46)

	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)
Age Groups	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3
Variables	log(1+# of GIRO Txns)			log(1+# of SAYE Txns)			log(1+S$ of Cash Withdrawal)		
$\widehat{\text{Distance to}}$ ATM	0.041**	0.028	0.009	0.026**	0.014	0.004	-0.026	-0.130*	-0.045
	(2.08)	(1.61)	(0.74)	(2.02)	(1.06)	(0.69)	(-0.52)	(-1.94)	(-1.04)

Table 8: The Effect of the ATM Closures on Customers' ATM Usage (First Stage)

We report panel regression estimates of the effect of ATM closure shocks on customers' total number of ATM transactions. The dependent variable is the log of 1+ the Total Number of ATM Transactions. The main independent variable is *Distance to ATM (Raw)*, a transaction-weighted distance to ATMs used from the provided customer address, instrumented by the ATM Closure Shock. We use *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. In Column (2), the main independent variable is *Favorite ATM Closure Shock* alone. Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels

	(1)	(2)
Variables	log(1+# of Total ATM Txns)	
Post Closure (Favorite ATM)	-0.058***	-0.059***
	(-16.12)	(-16.57)
Post Closure (Nearest ATM)	-0.001	
	(-0.56)	
Beginning Balance	0.0001***	0.0001***
	(8.64)	(8.639)
Monthly Salary	0.003***	0.003***
	(10.77)	(10.77)
Observations	5,994,130	5,994,130
R^2	0.654	0.654

Table 9: The Effect of ATM Usage on Digital Banking Activities (IV using ATM Closure Shock)

We report IV regression estimates of the effect of customers' total number of ATM transactions on digital banking activities using ATM closure shocks as an IV. Main independent variable is the log number of total ATM transactions, instrumented by *Post Closure (Favorite ATM)*. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. The dependent variable for Column (1) is the log of 1+ the Total Number of Digital Transactions, for Column (2) is the log of 1+ the Total Number of Financial Digital Transactions, for Column (3) is the log of 1+ the Total S$ Amount of Digital Transactions, and for Column (4) is the log of 1+ the Total Number of Account-level Transactions. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels

	(1)	(2)	(3)	(4)
	log(1+# of Digital Txns)		log(1+S$ of	log(1+# of
Variables	Total	Financial	Digital Txns)	Account Txns)
log(1+ # of $\widehat{\text{Total}}$ ATM Txns)	-0.693***	-0.361***	-1.003***	0.253***
	(-4.66)	(-4.69)	(-3.65)	(5.22)
Beginning Balance	0.0003***	0.0002***	0.001***	0.0003***
	(7.18)	(8.28)	(9.01)	(9.58)
Monthly Salary	0.006***	0.004***	0.017***	0.004***
	(9.12)	(9.51)	(10.04)	(10.44)
Observations	5,994,130	5,994,130	5,994,130	5,994,130
R^2	0.815	0.763	0.766	0.801

Figure 1: ATM Network in Singapore

We mark DBS bank's ATM network in Singapore for the 2015–2017 sample period. Blue dots represent building locations (postal codes) that have at least one ATM. Red dots are the 109 locations associated with ATM location closures in the sample period.

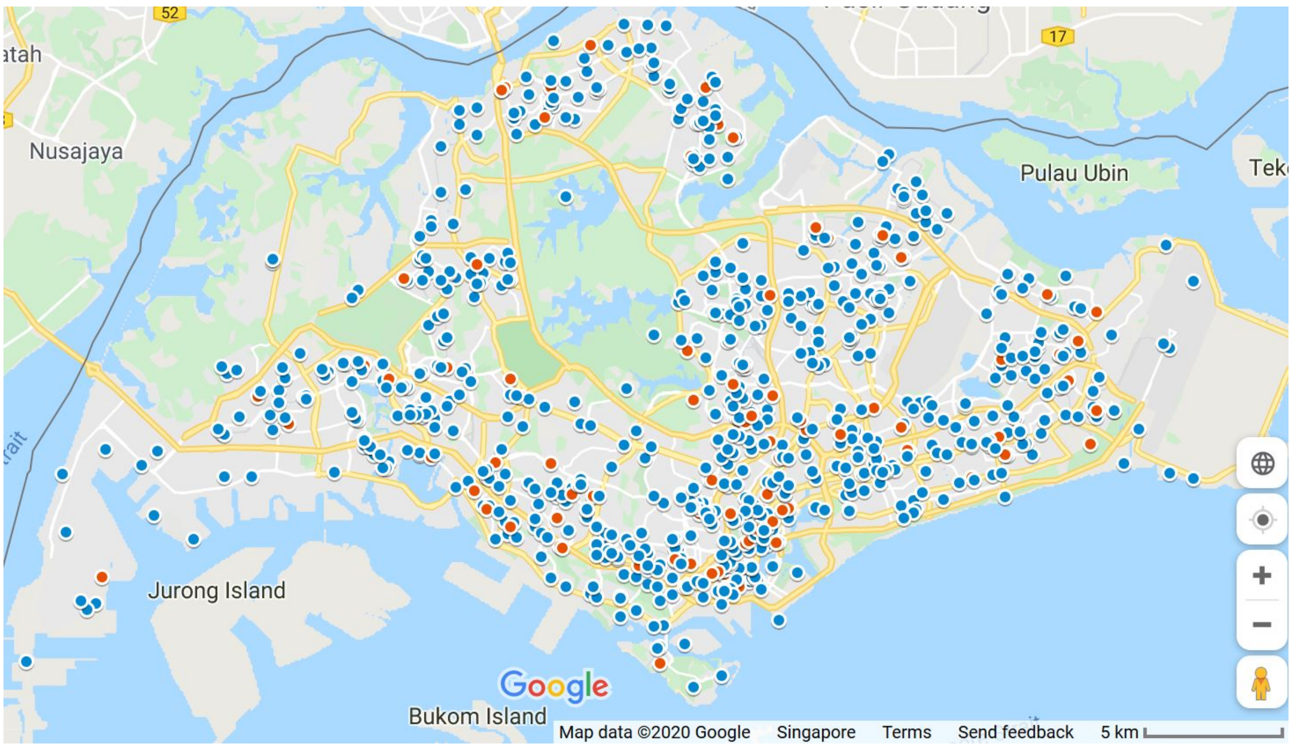


Figure 2: Distance to ATM by the Time of Usage

We report the time-series of the average *Distance to ATM* by the time of usage. We use the *Distance to ATM* which is a transaction-weighted distance to ATMs used from the provided customer address. The red dashed line represents the mean *Distance to ATM* during working hours. Working hours are defined as 8am to 6pm on weekdays except for public holidays. The blue solid line represents the average *Distance to ATM* during non-working hours in weekdays. The green long-dashed line represents the average *Distance to ATM* during weekends and public holidays. The distance averages are computed as follows. For each ATM transaction, we first compute a GPS distance between customer's address and ATM location. Using the total number of ATM transactions as the weight, we compute the weighted average distance per customer for each month. Observations where customers do not make any ATM transactions in that month are excluded. The sample is based on customers who had at least one salary credit or at least 6 months with auto-debt transactions in the 2015–2017 sample.

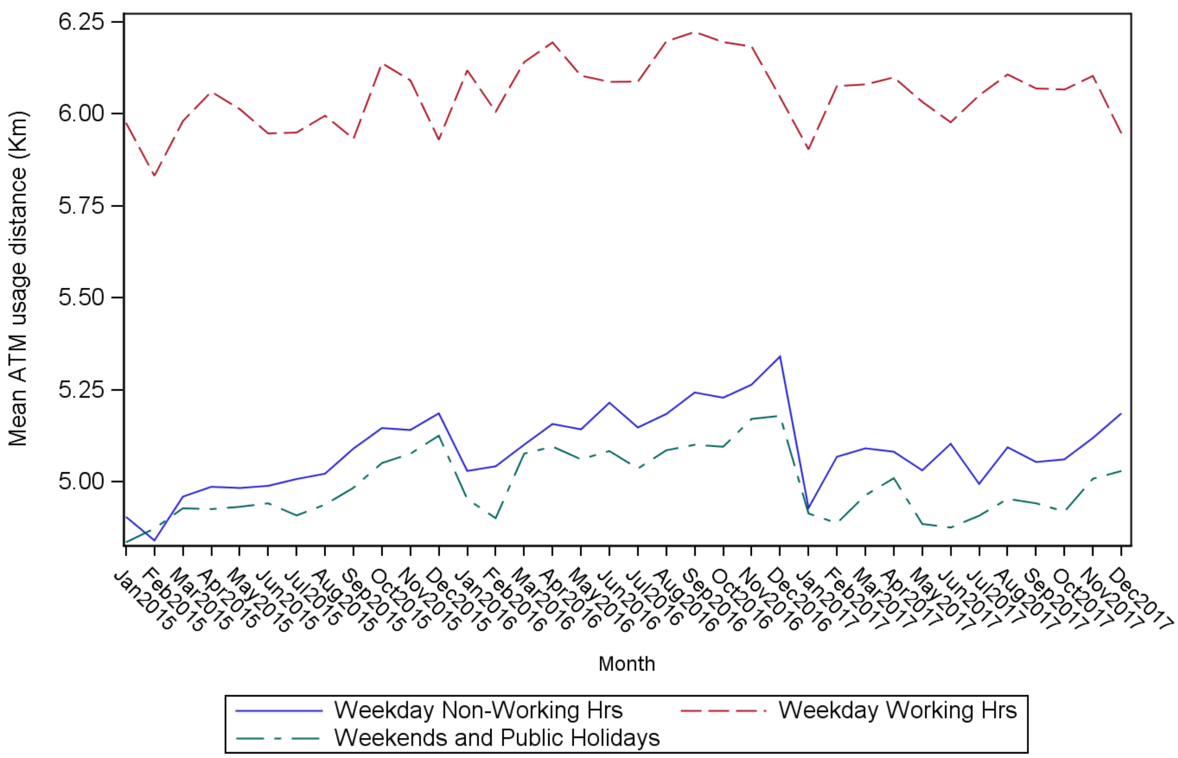
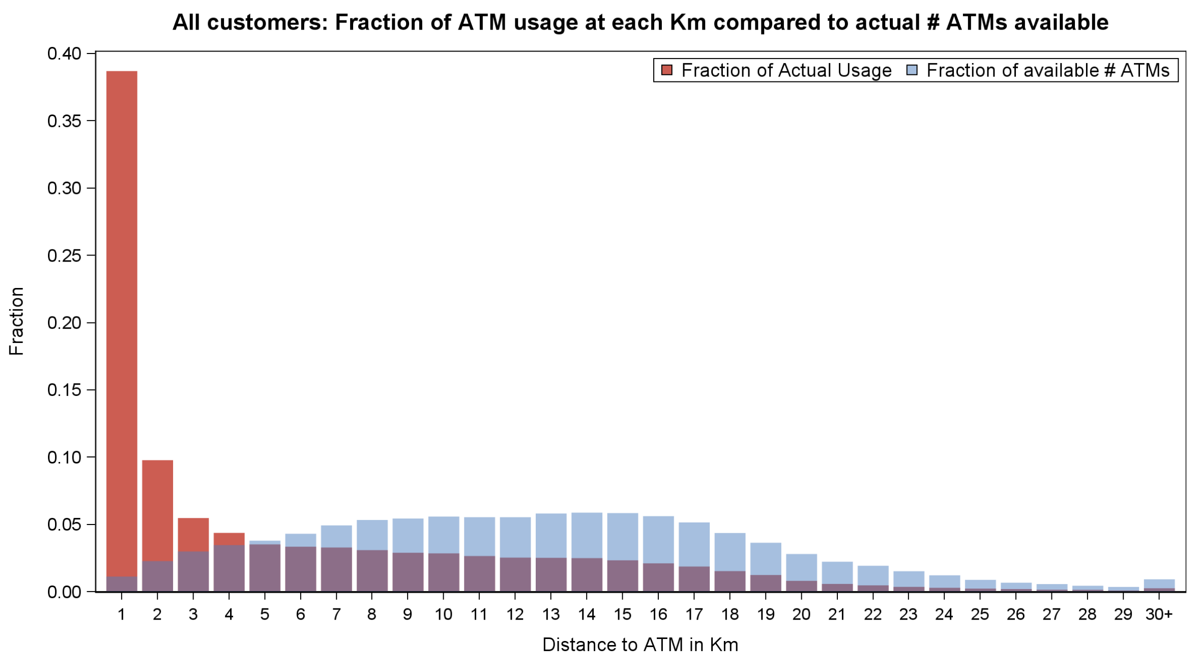


Figure 3: Distribution of ATM Usage by Distance

We report the average distribution of customers' ATM usage by the distance from customers' address. The top chart includes all customers in the sample based on customers who had at least one salary credit or at least 6 months with auto-debit transactions in the 2015–2017 sample. Red bars show the average fraction of a typical customers' ATM usage by the distance at each km. For comparison with the total number of ATMs available at each km, blue bars show the average fractions of available ATMs in Singapore by the distance from a typical customer's address. The bottom chart shows the average distribution of customers' actual ATM usage by distance for the subset of customers who provide a commercial address in the bank's record instead of a residential address. The address category is determined by searching for the postal code with an "(S) " prefix in streetdirectory.com.



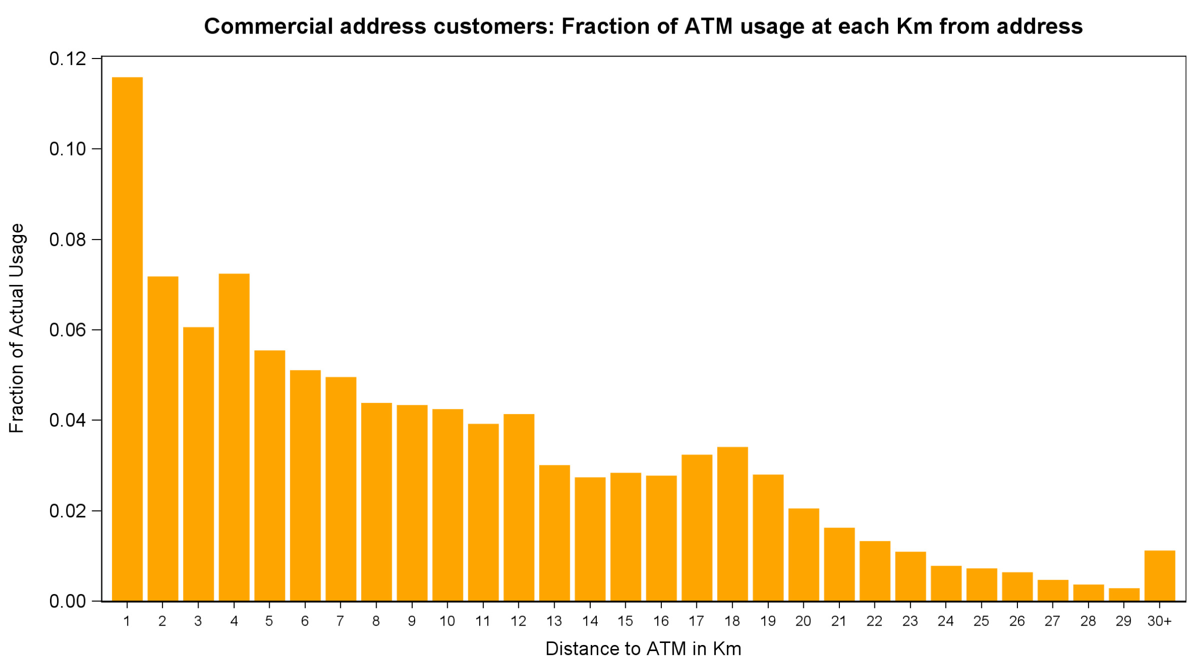


Figure 4: Customer-level Distribution of ATM Usage by Distance

We report the customer-level distribution of ATM usage by distance. We randomly select 1,000 customers who have auto-debit transactions in at least six of the sample months or at least one salary credit. They also must have at least five ATM transactions in the sample period. On the horizontal axis, the customers are arranged in increasing mean *Distance to ATM*. On the vertical axis, we report the fraction of ATM usage by distance for each customer. Each column hence represents an actual customer and the color intensity signifies the probability that the customer uses ATMs at that km from their provided address.

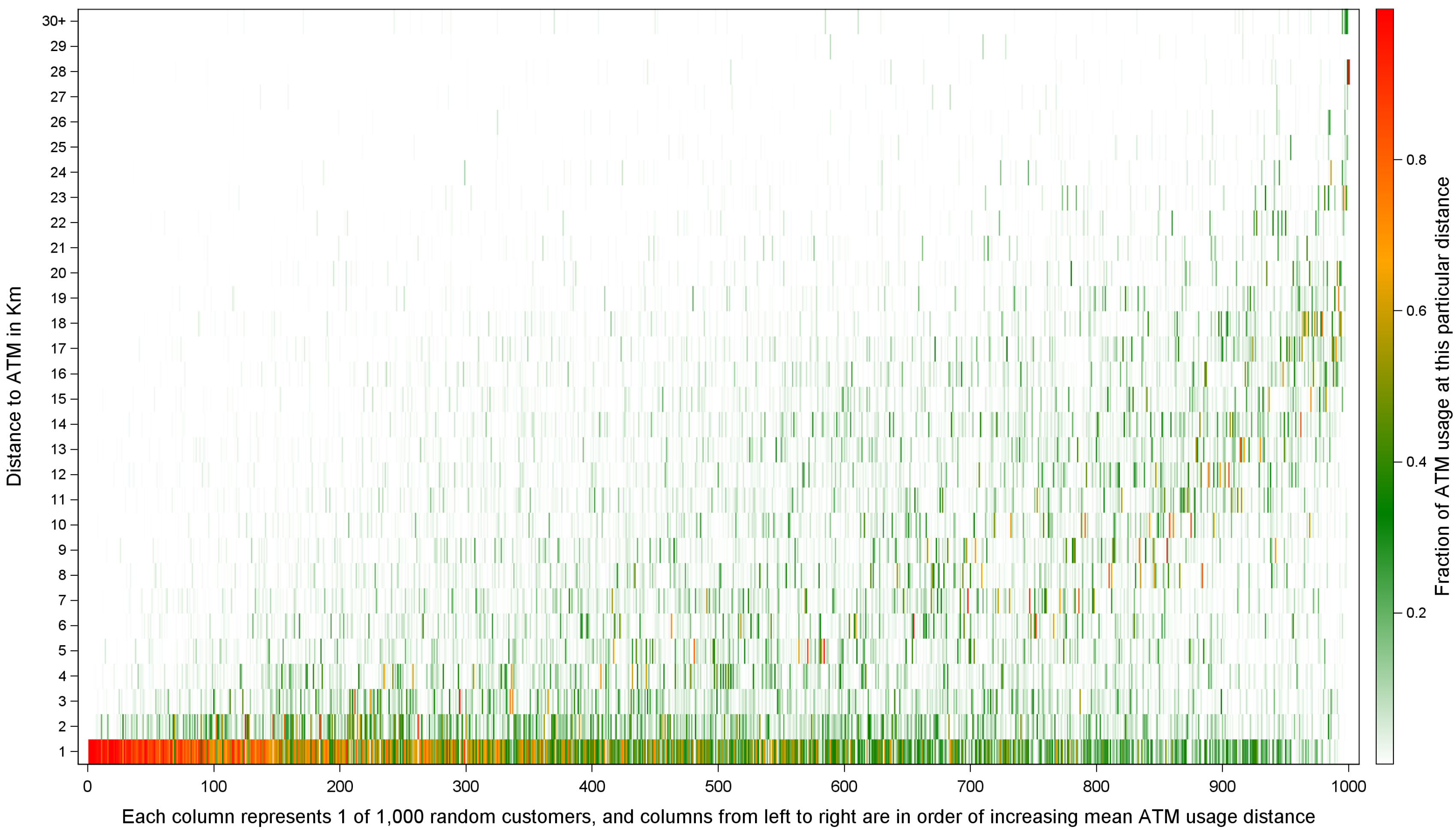


Figure 5: The Effect of Favorite ATM Closure on Distance to ATM

We report the residualized Distance to ATM before and after the closure of a customer's favorite ATM. We first regress the *Distance to ATM* on the *Post Closure (Nearest ATM)* that equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customers' postal address. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. We compute the average residual from the regression in the window of [-12, +12] months around the closure for customers who experience the closure of their favorite ATM. The blue line uses *Distance to ATM*, which is a transaction-weighted distance to ATMs used from the provided customer address.

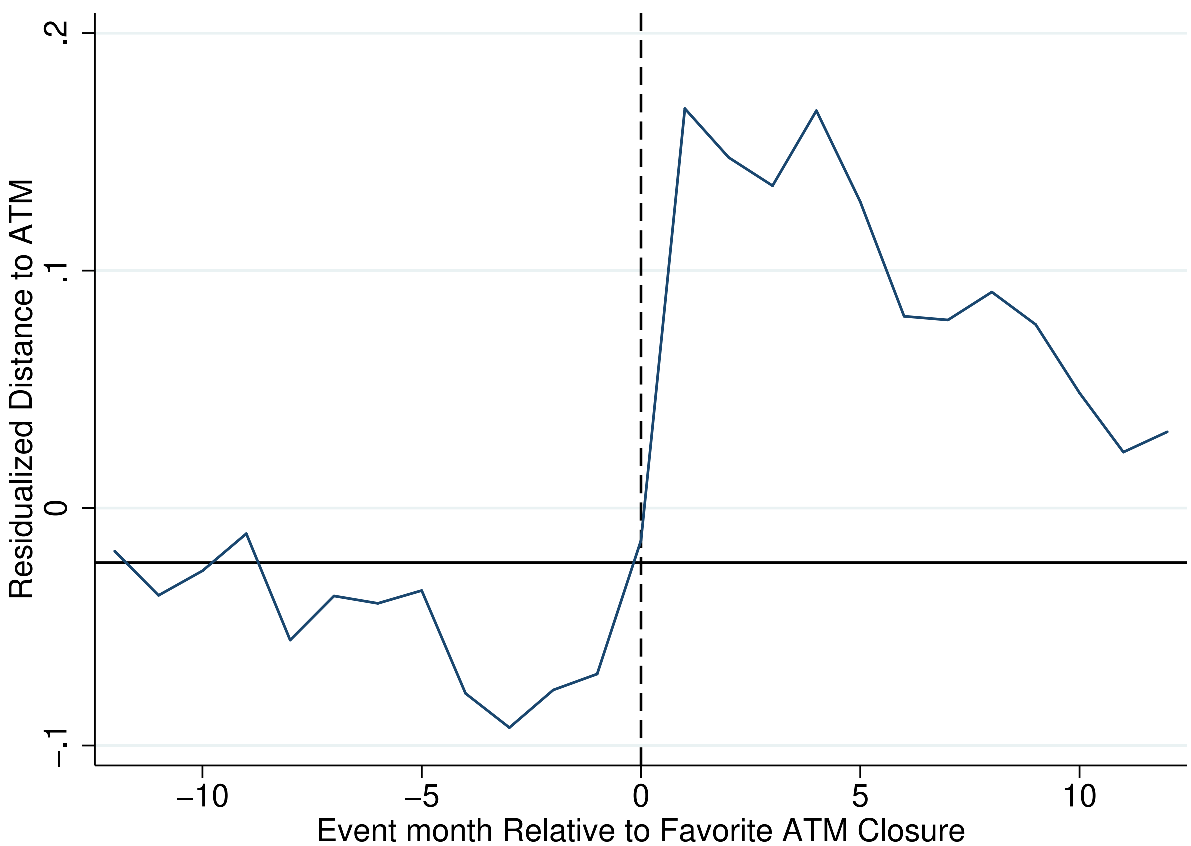


Figure 6: The Effect of Favorite ATM Closure on Customers' ATM Activity

We report the residualized ATM usage before and after the closure of a customer's favorite ATM. Panel A reports the average residual of log 1+ the Total Number of ATM Transactions before and after the closure of the customer's favorite ATM. We first regress log of 1+ the Total Number of ATM Transactions on the *Post Closure (Nearest ATM)* and other controls including monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. We then compute the average residual from the regression in the window of [-12, +12] months around the closure for customers who experience the closure of their favorite ATM. The blue line reports the average residuals and the red line reports the non-parametric fit of the average residuals (lowess). Panel B reports the average residual of the log of 1+ the Number of non-Financial ATM Transactions before and after the closure of the customer's favorite ATM, and Panel C reports the average residual of the log of 1+ the Average S$ Amount of an ATM Transaction before and after the closure of a customer's favorite ATM.

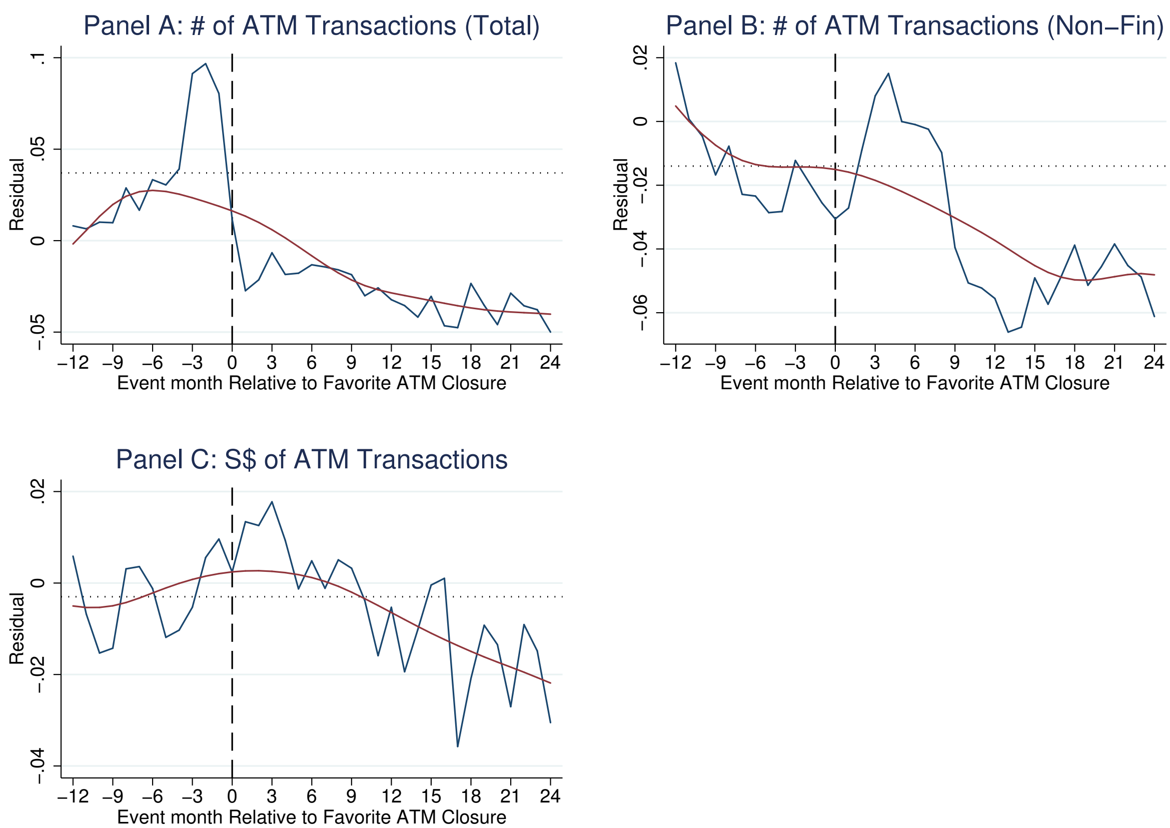


Figure 7: The Effect of Favorite ATM Closure on Customers' Digital Banking Activity

We report the residualized Digital banking activity before and after the closure of a customer's favorite ATM. Panel A reports the average residual of the log of 1+ the Total Number of Digital Transactions before and after the closure of a customer's favorite ATM. We first regress the log of 1+ the Total Number of Digital Transactions on the *Post Closure (Nearest ATM)* and other controls including monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. We then compute the average residual from the regression in the window of [-12, +12] months around the closure for customers who experience the closure of their favorite ATM. The blue line reports the average residuals and the red line reports the non-parametric fit of the average residuals (lowess). Panel B reports the average residual of the log of 1+ the Number of Financial Digital Transactions before and after the closure of customers' favorite ATM, and Panel C reports the average residual of the log of 1+ the Total S$ Amount of Digital Transactions before and after the closure of a customer's favorite ATM.

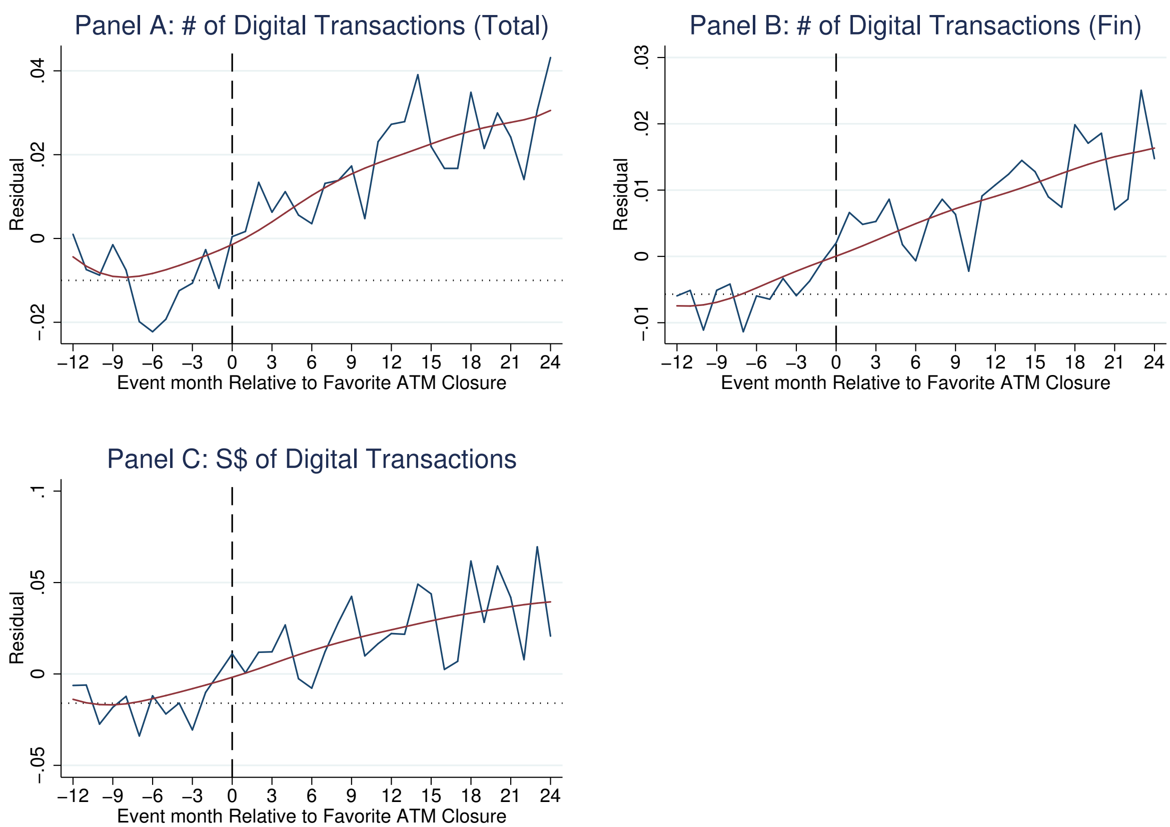


Figure 8: ATM transactions around Permanent and Temporary ATM Closures

We report the average number of ATM transactions around ATM closures by the type of ATM closures. We define an ATM closure as a temporary one if the ATM activity is non-zero in that postal code after the closure period. The rest of the ATM closures are assumed to be permanent closures. A red solid line plots the average number of ATM transactions around a permanent ATM closure. A blue dash line plots the average number of ATM transactions around a temporary ATM closure.